Development of a Wearable Electrical Impedance Tomographic Sensor for Gesture Recognition With Machine Learning

Citation for published version:
Yao, J, Chen, H, Xu, Z, Huang, J, Li, J, Jia, J & Wu, H 2019, 'Development of a Wearable Electrical Impedance Tomographic Sensor for Gesture Recognition With Machine Learning', *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 6, pp. 1550-1556. https://doi.org/10.1109/JBHI.2019.2945593

Digital Object Identifier (DOI):
10.1109/JBHI.2019.2945593

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
IEEE Journal of Biomedical and Health Informatics

Development of a Wearable Electrical Impedance Tomographic Sensor for Gesture Recognition with Machine Learning

Jiafeng Yao, Huaijin Chen, Zifei Xu, Jingshi Huang, Jianping Li, Jiabin Jia, Hongtao Wu

***Abstract*—A wearable electrical impedance tomographic (wEIT) sensor with 8 electrodes is developed to realize gesture recognition with machine learning algorithms. To optimize the wEIT sensor, gesture recognition rates are compared by using a series of electrodes with different materials and shapes. To improve the gesture recognition rates, several Machine Learning algorithms are used to recognize three different gestures with the obtained voltage data. To clarify the gesture recognition mechanism, an electrical model of the electrode-skin contact impedance is established. Experimental results show that: rectangular copper electrodes realize the highest recognition rate; the existence of the electrode-skin contact impedance could improve the gesture recognition rate; Medium Gaussian SVM (Support Vector Machine) algorithm is the optimal algorithm with an average recognition rate of 95%.**

***Index Terms*—Wearable sensor, Electrical impedance tomography, Machine learning, Gesture recognition, Contact impedance**

I. Introduction

ELECTRICAL Impedance Tomography (EIT) has the advantages of non-invasive, non-hazardous, simple structure and low cost [1]. It has been successfully applied to clinical monitoring of pulmonary respiratory functions [2-4]. EIT technique is utilized to study the changes in the internal conductivity of the human body, and then infer the physiological state of the human body from the changes in the internal conductivity of the human body [5]. The reconstructed images by EIT contain a wealth of anatomical information, from which, electrical properties of different tissues under different physiological conditions can be obtained [6, 7].

Manuscript received **; revised **; accepted **. This work was supported in part by the National Natural Science Foundation of China under Grant 51706098, in part by the Natural Science Foundation of Jiangsu Province under Grant BK20170792, in part by The Royal Society - International Exchanges 2018 Cost Share (China), IEC\NSFC\181213. The associate editor coordinating the review of this paper and approving it for publication was **. (*Corresponding author: Jiafeng Yao*)

J. Yao, H. Chen, Z Xu, H. Wu are with the College of Mechanical & Electrical Engineering, Nanjing University of Aeronautics & Astronautics, Nanjing 210016, China. (e-mail: jiaf.yao@nuaa.edu.cn)

J. Huang is with Humanomics LAB, Sino-Korean School of Multimedia Design, Shanghai University of Engineering Science, Shanghai, 201620 China.

J. Li is with the College of Engineering, Zhejiang Normal University, Jinhua 321004 China.

J. Jia is with the Agile Tomography Group, Institute for Digital Communications, School of Engineering, The University of Edinburgh, Edinburgh, EH9 3JL, UK.

Color versions for one or more of the figures in this paper are available online at ****.

Digital Object Identifier ****.

With the development, the traditional touch and mouse and keyboard human-computer interaction methods are not enough to meet the requirements. More convenient human-computer interaction approach is required. Gesture recognition is an important means of human-computer interaction. Gesture recognition is one of the effective approaches to realize humanized interaction [8]. The existing gesture recognition approach mainly includes two major categories, which are machine vision technology and sensor technology [9].

Machine vision is a technique that uses a camera to capture images of human motion and uses image processing techniques to resolve position and pose [10]. First, the image of the experimental object is detected and collected, and the feature information is extracted from the acquired image. Then, based on the extracted feature information, a training model is established, such as Hidden Markov model (HMM). Finally, the trained model is applied to perform gesture recognition on the image information collected later [11]. Machine vision technology is relatively mature, and a large number of products have been applied to the market, such as LEAP MOTION's 3D motion controller. Itkarkar et al. concluded that the existing challenges of machine vision technology are complex gestures and occlusion problems [12]. The advantage of machine vision is that it does not require the subject to wear the sensing device, and the recognition rate is high. The disadvantage is that it is susceptible to external environment (such as light, color), and gestures will be blocked during motion to lose information. For example, if a person controls an unmanned drone in the case of outdoor movement, it may be out of the scope of the camera. At this time, it is not suitable to use machine vision recognition gestures, and sensor technology can be applied.

Sensor technology mainly includes surface myoelectric sensors and motion sensors. The surface myoelectric sensor uses the electrodes placed on the surface of the skin to collect bioelectrical signals generated when the human body moves. Tang et al. developed a multi-channel surface electromyogram (sEMG) sensor for multi-hand movement recognition [13]. Samadani et al. developed an inter-individual gesture recognition model based on Hidden Markov Model, which receives surface EMG signals as input and predicts corresponding gestures [14]. Bioelectrical signals contain a wealth of information, and the accuracy of static gesture recognition is high. However, the surface EMG sensor cannot capture large-scale motion. Even the bioelectrical signals collected are complex, making it difficult to analyze accurately. The motion sensor reconstructs the motion trajectory by capturing the acceleration and angular velocity information during the movement of the human body [15]. Gupta et al. used accelerometers and gyroscopes to identify continuous gestures [16]. The advantage of the motion sensor is that it is suitable for dynamic gesture recognition and is not easily restricted by the external environment. However, it has low sensitivity to low-speed motion and contains limited gesture information.

Different gestures in the wrist cause a movement of the internal muscle tissue and bone, which changes the internal conductivity distribution of the arm. EIT could reconstruct the internal conductivity distribution of the arm. Since the electrode sensor of the EIT is attached to the skin surface like the myoelectric sensor, it has the advantage of being unaffected by the external environment as compared with machine vision. In the EIT method, current source is applied to a pair of electrodes, voltage signals are detected and processed from other electrodes. In this case, the signal is easier to identify than bioelectrical signal.

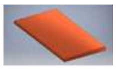
In the present study, a wearable Electrical Impedance Tomographic (wEIT) sensor is proposed to realize the gesture recognition by combining the sensor technology and the EIT technology. To clarify the optimal material of the wEIT sensor, the recognition rates using a series of electrodes with different materials and shapes are compared in the experiments. Then, several machine learning algorithms are used to improve the recognition rate. Moreover, an electrical model of the electrode-skin contact impedance is established to clarify the gesture recognition mechanism. Finally, the optimal material and algorithm are used to recognize three different gestures.

II. Gesture Recognition Detection System

A. *The wearable Electrical Impedance Tomographic (wEIT) sensor*

The wearable Electrical Impedance Tomographic (wEIT) sensor is fabricated with 8 electrodes and an elastic bandage. The electrodes are used to inject an excitation current signal and collect the correspond voltage signal. Several issues should be considered, such as the comfort of wearing, the larger contact area between the electrode and the skin, the lower contact impedance between the electrode and the skin. Contact impedance produces larger noise in the measurement, which will decrease the recognition rate [17]. The contact impedance can be reduced by the following two aspects: increasing the pressure and contact area between the electrode and the skin; applying a certain amount of medical conductive fluid on the skin in contact with the electrode. During this experiment, the measurement time is long, and the conductive fluid may be dried during the experiment, resulting in inaccurate results. In this experiment, conductive gel is used instead of conductive fluid for the medical electrode.

TABLE I
ELECTRODE SENSOR COMPARISON

Electrode Material	3D Model	Contact Area /mm^2	Fixed Way	Conductive Fluid
Rectangular Copper Electrode		11×15	Elastic Bandage	No
Curved Copper Electrode		16π	Elastic Bandage	No
Conductive Cloth Electrode		10×14	Elastic Bandage	No
Medical Electrode		16π	Medical Tape	Have

Since materials and shapes of the wEIT sensor greatly affect the gesture recognition rate, the electrodes used in the experiment are mainly divided into three categories: copper electrodes, conductive cloth electrodes and medical electrodes as shown in Table I. The conductive liquid is self-contained on the medical electrode. The medical electrodes are produced by Hangzhou Xunda Radio Equipment Co., Ltd. The copper electrodes are divided into curved electrodes and rectangular electrodes.

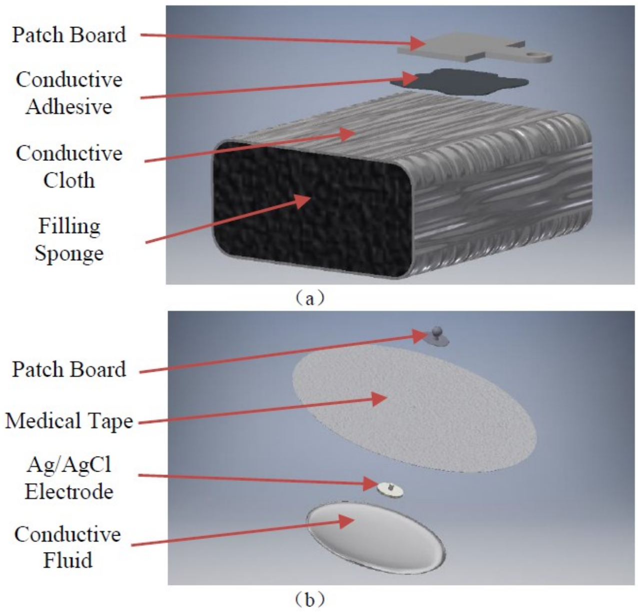


Fig. 1 Electrode structure, (a) conductive cloth electrode, (b) medical electrode.

The rectangular copper electrode has a large contact area and has a good uniformity of electric field distribution. The curved copper electrode contact surface has a curved surface, which can reduce the gap between the electrode and the skin. Especially, the details of the conductive cloth electrode and the medical electrode are shown in Fig. 1.

B. *Gesture recognition system*

Fig. 2 shows the experimental set-up of the gesture recognition, which includes a Red Pitaya STEMlab, a high output impedance Voltage Controlled Current Source (VCCS), a high performance analog multiplexer modules, electrode array sensors and a PC [5]. The computer sends a command to Red Pitaya STEMlab to generate a sinusoidal AC voltage signal with a frequency from f = 0 Hz to f = 200 KHz with an amplitude of $V_m = \pm 1$ V; the VCCS module is used to convert the voltage signal into a stable sinusoidal AC current signal; the current signal is injected into the electrode pair of the bracelet through the analog multiplexer module; the voltage signals of the remaining electrodes pass through the analog multiplexer module. The voltage signal is collected by Red Pitaya STEMlab and transmitted to the computer for image reconstruction with an image reconstruction algorithm.

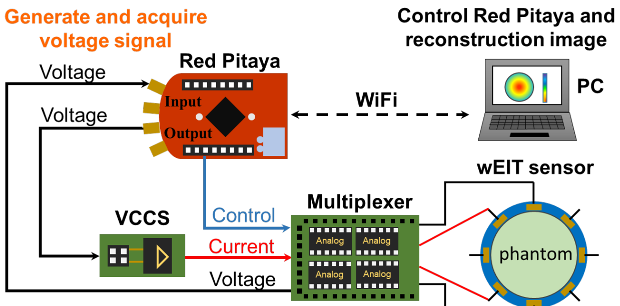


Fig. 2 Experimental set-up of EIT gesture recognition.

C. *Electrical model of electrode-skin contact impedance for gesture recognition*

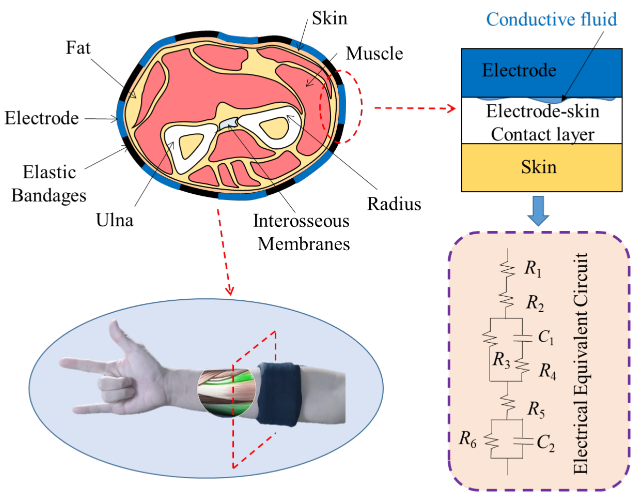


Fig. 3 Electrical model of electrode-skin contact impedance for gesture recognition.

An electrical model of electrode-skin contact impedance for gesture recognition is established in Fig. 3. A contact impedance is generated between the electrode and the skin, which mainly contains a body fluid and air. The contact impedance greatly increases the electrical conductivity between the electrode and the skin, even reaches 10~100 times. In the meantime, the contact impedance changes with the arm movement, which provide a potential approach to capture the electrical signal change of the gesture. The established electrical equivalent circuit in Fig. 3 provide a basic model to explain the electrode-skin contact impedance in the experiments.

D. *Image reconstruction algorithm*

Some exploratory work has been carried out to solve the inverse problem with image reconstruction algorithms for EIT [18-21]. The image reconstruction algorithm used in this paper is generalized vector sampled pattern matching (GVSPM), which is an algorithm for solving linear equations through iteration. Conventional iterative algorithms have drawbacks [19]. GVSPM is a target criterion based on the minimum angle between the input vector and the solution vector, which effectively overcomes the drawbacks of the iterative algorithm. The GVSPM solution contains an objective function and converges without any empirical value [22]. The objective function F of the k-th iterative particle distribution $\sigma^{(k)}$, $f(\sigma^{(k)})$ is given by:

$$F = f(\sigma^{(k)}) = U'^{(\exp)}\, U'^{(k)} \rightarrow 1.0 \qquad (1)$$

Where $U^{(\exp)}$ is the voltage vector from experiment, $U^{(k)}$ is the voltage vector from the k-th iteration, (′) is the normalized quantities.

III. EXPERIMENTAL METHOD

A. *Gesture measurement method*

Three subjects were recruited to measure the gesture by using the wEIT sensor and the developed EIT system. Three gestures of the right hand are measured, which are a fist, palm open (five fingers close together) and palm bent (the same five fingers are close together and the wrist is bent to the right), as shown in Fig. 4. In order to control the influences of the variables, the subjects are all 20 to 25 adult males to ensure that the skin tissue, water content and other factors are relatively stable. The test area should be cleaned before the experiment. All the experimental data of the same person under the same electrode in this experiment were obtained in one measurement, to reduce the changes of the contact impedance caused by changing of wearing position and contact condition between the electrodes and the skin. In order to ensure the consistency of the experimental data, different kinds of electrode positions need to be marked on the bracelet sensors and the skin of the subject to ensure that the relative positional deviation of the electrodes is minimized. Each subject was measured 10 times for each gesture.

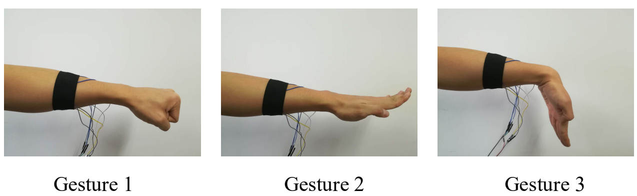


Fig. 4. Three measured gestures in the experiments, Gesture 1, a fist, Gesture 2, palm open, Gesture 3, palm bent.

Classification learner, a toolbox of MATLAB, is used to recognize different gestures. There are three kinds of gestures, 10 sets of data for each gesture, each containing 40 obtained voltage data. For defined validation method, the default Ross-Validation option is used in training, in which Cross-Validation folds is 5 folds and MATLAB uses hands. An operation process is: select a number of folds (or divisions) to partition the data set using the slider control, if you choose k folds, then the app: 1, Partitions the data into k disjoint sets or folds; 2, For each fold: 2a, Trains a model using the out-of-fold observations, 2b, Assess model performance using in-fold data; 3, Calculates the average test error over all folds.

This method gives a good estimate of the predictive accuracy of the final model trained with all the data. It requires multiple fits but makes efficient use of all the data, so it is recommended for small data sets.

B. Contact impedance detection

The collected signal in the gesture measurements consist of three parts: internal changes in the arm section, changes in section shape, and changes in contact impedance [17]. The state change of the human arm bones and muscles is the reason why the human body can make different gestures. The internal state and cross-sectional shape of different arm sections correspond to different gestures one by one.

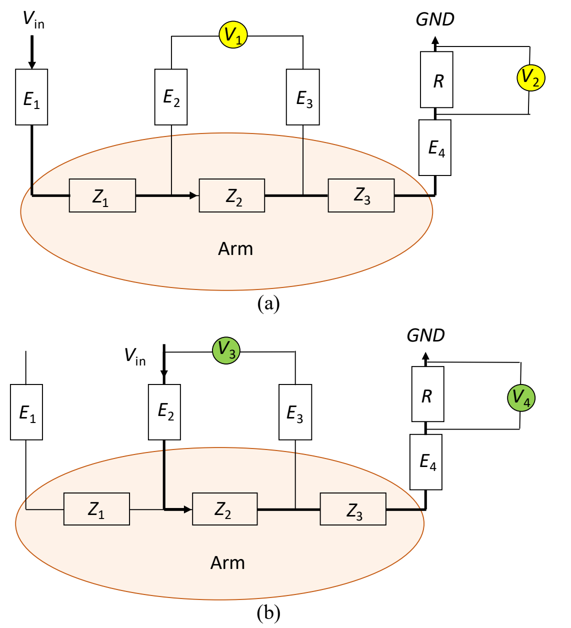


Fig. 5. Calculation method of the electrode-skin contact impedance.

The objective is to reconstruct the internal cross sectional shape of the arm for gestures and to identify different gestures. In EIT measurement process, the contact between the electrode and the skin will produce contact impedance, and the contact impedance is affected by factors such as pressure and size of contact area. The contact impedance changes during the different gesture measurement processes [23]. The four-electrode measurement method is used to the measurement of the electrode-skin contact impedance. Fig. 5 shows the calculation model of the electrode-skin contact impedance [24].

As shown, E_1, E_2, E_3, and E_4 indicate the contact impedance between the four electrodes and the skin, respectively. Z_1, Z_2, Z_3 represent the internal impedance of the arm, R represents the external standard resistance, and V_{in} represents the voltage signal of the excitation. In Fig. 5(a), the current I through the human body and the impedance Z_2 inside the arm:

$$I = V_2/R \tag{2}$$

$$Z_2 = V_1/I \tag{3}$$

From Figure 5(b):

$$I = V_4/R \tag{4}$$

$$E_2 + Z_2 = V_3/I \tag{5}$$

The contact impedance E_2 is calculated from Eqs. (4)-(7):

$$E_2 = (V_3 \times R)/V_4 - (V_1 \times R)/2 \tag{6}$$

IV. Experimental Result

A. Gesture recognition measurement result

Six subjects were recruited to participate in the experiment. The electrical impedances were measured under different gestures. Each subject wear the wEIT at the wrist. The voltage data of the three gestures for each electrode pair are shown in Fig. 6. The shapes of the three sets of waveforms are roughly similar, but the voltage amplitude value of different gestures are very different, and the gesture can be identified based on these measured data.

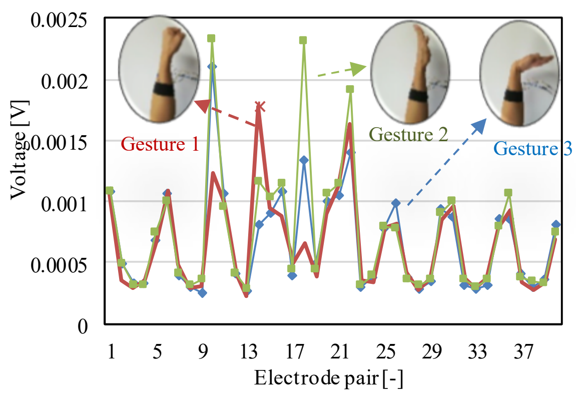
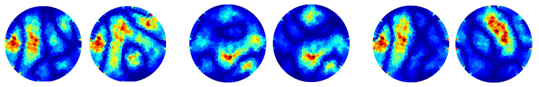
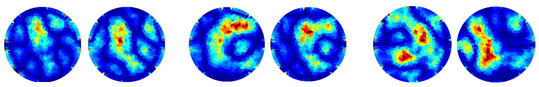
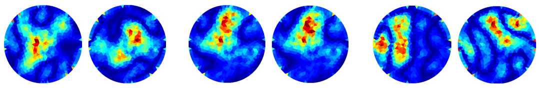
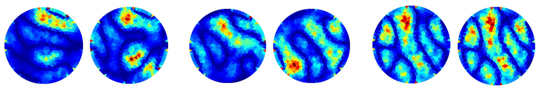


Fig. 6. Voltage comparison of three gestures among a series of electrode pair.

When the voltage data of the Gesture 1 was used as a reference, the voltage data of the Gesture 2 and the voltage data of the Gesture 3 are respectively subtracted from the voltage data of the Gesture 1. The reconstructed image of the wrist cross-section with the Generalized Vector Sampled Pattern Matching (GVSPM) algorithm as shown in TABLE II.

Without changing the position of the wEIT sensor, the three gestures of three subjects were measured 10 times each, using classification learning toolbox in MATLAB for gesture recognition [25]. The recognition rate of gesture recognition was different with different electrodes (TABLE I). The recognition rate is the highest with the rectangular copper electrode, which can reach an average of 98%. The recognition rate under medical electrode is the lowest, with an average of

TABLE II
RECONSTRUCTED IMAGE OF DIFFERENT GESTURES

Electrode Material	Subject 1		Subject 2		Subject 3	
	2~1	3~1	2~1	3~1	2~1	3~1
Rectangular Copper Electrode						
Curved Copper Electrode						
Conductive Cloth Electrode						
Medical Electrode						

only about 80%. Different machine learning algorithms also produce different recognition rates. The final results are shown in Table III.

B. *Contact impedance detection results*

In order to observe the influence of contact impedance, the contact impedance was measured with medical electrodes and rectangular copper electrodes from f = 10 kHz to f = 1 MHz. The input voltage is 0.1 V. The reference resistance R = 200 Ω is used for medical electrode measurement, and there is conductive fluid between the electrode and the skin; the reference resistance R = 1000 Ω is used for rectangular copper electrode measurement. There is no conductive fluid between the electrode and the skin. The final measured contact impedance is shown in Fig. 8. The contact impedance by rectangular copper electrode is higher than that of the medical electrode, which means that, if the contact impedance could be used to observe the changes of the gesture, rectangular copper electrode is a better choice.

TABLE III
THE HIGHEST RECOGNITION RATE WITH A SERIES OF MACHINE LEARNING ALGORITHMS USING DIFFERENT ELECTRODES

	Subject 1	Subject 2	Subject 3
Conductive Cloth Electrode	90.0% (SVM, Ensemble)	96.7% (SVM, Quadratic Discriminant, Ensemble)	90.0% (SVM)
Rectangular Copper Electrode	96.7% (SVM, Quadratic discriminant)	96.7% (SVM, Ensemble)	100% (SVM, KNN)
Curved Copper Electrode	96.7% (Ensemble)	93.3% (SVM, KNN)	100% (Ensemble)
Medical Electrode	86.7% (SVM)	76.7% (SVM)	76.7% (SVM, Ensemble)

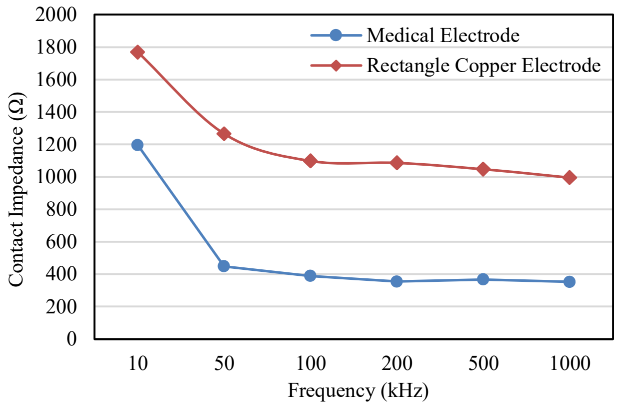


Fig. 7. Relationship between contact impedance and input voltage frequency.

V. DISCUSSION

A. *Influence of the contact impedance*

The contact impedance detection was carried out by four-electrode method. The contact impedance decreases with the increase of the frequency of the input excitation signal and decreases obviously at 50 kHz, but as the frequency continues to rise and the contact impedance tends to stabilize, it can be considered that the capacitive component of the contact impedance has basically disappeared. The input signal used by EIT is a current signal, and a voltage-controlled current source (VCCS) is required to convert the voltage signal output from the FPGA to a current signal. The ideal VCCS output resistance should be infinite, but in practical engineering, the VCCS output resistance decreases with the increase of frequency, and the high frequency will make the VCCS no longer be the constant current source. Therefore, it is reasonable to choose the input excitation signal frequency at f = 50 kHz in the gesture recognition experiment. Moreover, from f = 50 kHz, the contact impedance becomes stable (Fig. 7).

In the experiment, the contact impedance was reduced when the conductive fluid was used in the medical electrode (Fig. 7). However, a less contact impedance makes the gesture recognition more difficult. Therefore, we conclude from the experiment that, a proper contact impedance helps to improve the gesture recognition rate.

B. *Gesture recognition considering contact impedance*

The contact impedance is considered to play an important role in gesture recognition. When different gestures are made, internal muscle changes lead to changes in the internal conductivity distribution. At the same time, skin deformation generates a different contact impedance between the electrode and the skin. The different voltage data that caused by different gestures is the superimposing of the two voltage changes that caused by the two changes above. Although the contact impedance by the copper chip is large, when different gestures are made, the contact impedance changes greatly when the gesture changes, leading to a higher recognition rate. On the other hand, when the contact impedance caused by medical electrode is small, the contact impedance change is also small as the gesture changes, leading to a lower recognition rate. That is to say, the ability of gesture recognition contains two factors, one is the muscle change in the wrist, the other is the contact impedance between electrode and skin.

In order to select the optimal algorithm, a series of algorithms in Matlab machine learning toolbox are used experimentally in this paper. Among these algorithms, the Medium Gaussian SVM, Bagged Trees Ensemble and Quadratic Discriminant algorithms show good results. Fig. 8 is the recognition rate of these three algorithms for the subjects when using rectangular copper electrode. The Medium Gaussian SVM algorithm can be obtained by graph with an average recognition rate of 97.8%, which is higher than the Bagged Trees Ensemble algorithm (average 92.2%) and the Quadratic Discriminant algorithm (average 95.6%). These results shows that the Medium Gaussian SVM algorithm is the optimal algorithm for gesture recognition.

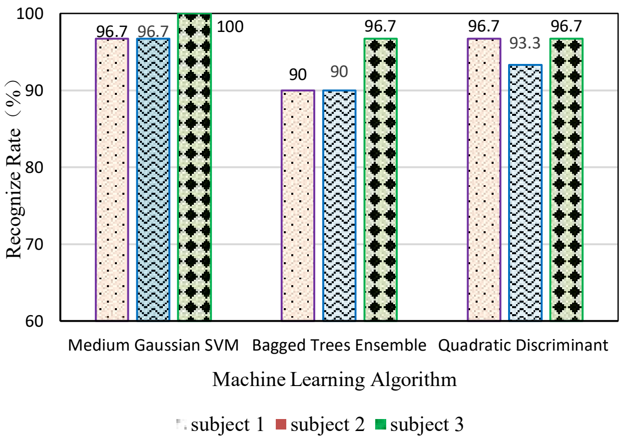


Fig. 8 Gesture recognition rate of three algorithms when using rectangular copper electrodes.

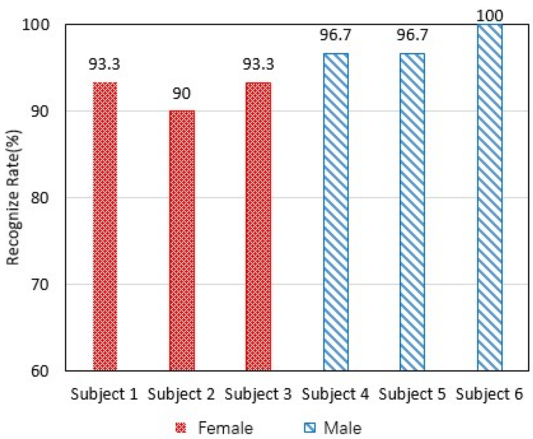


Fig. 9 Gesture recognition rate among six subjects with SVM.

Fig. 9 shows the gesture recognition rates among six subjects with Medium Gaussian SVM. The six subjects include three females and three males. The average recognition rate is 95%, which is higher than the related research by Yang et al. [26]. Because this study applied the original voltage data to recognize the gesture. In Yang et al.'s study, they firstly reconstructed the image, then recognize the gesture from the reconstructed images. The EIT image reconstruction is an inverse problem to solve an ill-conditioned matrix, which ineluctability decreases the recognition rate.

In summary, EIT can be used for gesture recognition technology, the key problem to be solved is how to control the stability of contact impedance, that is, when in the static measurement, the contact impedance changes should be as small as possible; when the gesture changes, a proper contact impedance should be used.

VI. CONCLUSION

A wearable EIT sensor has been developed for gesture recognition. The results are concluded as follows:

(1) The wEIT sensor with 8 electrodes was developed. Four kinds of electrodes were studied to find the optimum material and shape, including conductive cloth electrode, rectangular copper electrode, curved copper electrode and medical electrode. The rectangular copper electrode is selected as the optimal electrode.

(2) An electrical model of the electrode-skin contact impedance is established to clarify the influence of the contact impedance on the gesture recognition rate. The rectangular copper electrode induces a proper contact impedance, which contributes to a higher gesture recognition rate.

(3) Several Machine Learning algorithms are used to recognize three different gestures. The Medium Gaussian SVM (Support Vector Machine) algorithm is the optimal algorithm with an average recognition rate of 95%.

ACKNOWLEDGMENT

The authors wish to thank Prof. Masahiro Takei of Chiba University for his technical support.

REFERENCES

[1] J. Yao, and M. Takei, "Application of Process Tomography to Multiphase Flow Measurement in Industrial and Biomedical Fields: A Review," *IEEE Sensors Journal,* vol. 17, no. 24, pp. 8196-8205, Dec 15, 2017.

[2] J. Jia, M. Wang, H. I. Schlaberg *et al.*, "A novel tomographic sensing system for high electrically conductive multiphase flow measurement," *Flow Measurement & Instrumentation,* vol. 21, no. 3, pp. 184-190, 2010.

[3] S. Ren, Y. Wang, G. Liang *et al.*, "A Robust Inclusion Boundary Reconstructor for Electrical Impedance Tomography With Geometric Constraints," *IEEE Transactions on Instrumentation and Measurement,* vol. 99, pp. 1-12, 2018.

[4] S. Ren, K. Sun, D. Liu *et al.*, "A Statistical Shape Constrained Reconstruction Framework for Electrical Impedance Tomography," *IEEE Transactions on Medical Imaging*, pp. 1-1, 2019.

[5] Z. Xu, J. Yao, Z. Wang *et al.*, "Development of a Portable Electrical Impedance Tomography System for Biomedical Applications," *IEEE Sensors Journal,* vol. 18, no. 19, pp. 8117-8124, 2018.

[6] T. K. Bera, J. Nagaraju, and G. Lubineau, "Electrical impedance spectroscopy (EIS)-based evaluation of biological tissue phantoms to study multifrequency electrical impedance tomography (Mf-EIT) systems," *Journal of Visualization*, pp. 1-23, 2015.

[7] D. Liu, and J. Du, "A moving morphable components based shape reconstruction framework for electrical impedance tomography," *IEEE Trans Med Imaging*, May 23, 2019.

[8] Y. Lee, B. Nicholls, L. D. Sup *et al.*, “Soft Electronics Enabled Ergonomic Human-Computer Interaction for Swallowing Training,” *Scientific Reports,* vol. 7, pp. 46697, 2017.
[9] S. S. Rautaray, and A. Agrawal, “Vision based hand gesture recognition for human computer interaction: a survey,” *Artificial Intelligence Review,* vol. 43, no. 1, pp. 1-54, 2015.
[10] O. K. Oyedotun, and A. Khashman, “Deep learning in vision-based static hand gesture recognition,” *Neural Computing & Applications*, pp. 1-11, 2016.
[11] C. L. Huang, and S. H. Jeng, “A model-based hand gesture recognition system,” *Machine Vision & Applications,* vol. 12, no. 5, pp. 243-258, 2001.
[12] R. R. Itkarkar, and A. V. Nandi, "A survey of 2D and 3D imaging used in hand gesture recognition for human-computer interaction (HCI)."
[13] T. Xueyan, L. Yunhui, L. Congyi *et al.*, “Hand motion classification using a multi-channel surface electromyography sensor,” *Sensors,* vol. 12, no. 2, pp. 1130, 2012.
[14] A. A. Samadani, and D. Kulic, “Hand gesture recognition based on surface electromyography,” in Engineering in Medicine & Biology Society, 2014.
[15] S. Zhou, Z. Dong, W. J. Li *et al.*, “Hand-written character recognition using MEMS motion sensing technology,” in IEEE/ASME International Conference on Advanced Intelligent Mechatronics, 2008.
[16] H. P. Gupta, H. S. Chudgar, S. Mukherjee *et al.*, “A Continuous Hand Gestures Recognition Technique for Human-Machine Interaction Using Accelerometer and Gyroscope Sensors,” *IEEE Sensors Journal,* vol. 16, no. 16, pp. 6425-6432, 2016.
[17] A. Boyle, and A. Adler, “The impact of electrode area, contact impedance and boundary shape on EIT images,” *Physiological Measurement,* vol. 32, no. 7, pp. 745, 2011.
[18] D. Liu, D. Smyl, and J. Du, “A Parametric Level Set-Based Approach to Difference Imaging in Electrical Impedance Tomography,” *IEEE Trans Med Imaging,* vol. 38, no. 1, pp. 145-155, Jan, 2019.
[19] M. Takei, “GVSPM image reconstruction for capacitance CT images of particles in a vertical pipe and comparison with the conventional method,” *Measurement Science and Technology,* vol. 17, no. 8, pp. 2104, 2006.
[20] W. Yang, and L. Peng, “Image reconstruction algorithms for electrical capacitance tomography,” *Measurement Science and Technology,* vol. 14, no. 1, pp. R1, 2002.
[21] D. Liu, A. K. Khambampati, and J. Du, “A Parametric Level Set Method for Electrical Impedance Tomography,” *IEEE Trans Med Imaging,* vol. 37, no. 2, pp. 451-460, Feb, 2018.
[22] X. Liu, J. Yao, Y. Cui *et al.*, “Image Reconstruction under Contact Impedance Effect in Micro Electrical Impedance Tomography Sensors,” *IEEE Transactions on Biomedical Circuits and Systems*, 2018.
[23] V. Marozas, A. Petrenas, S. Daukantas *et al.*, “A comparison of conductive textile-based and silver/silver chloride gel electrodes in exercise electrocardiogram recordings,” *Journal of Electrocardiology,* vol. 44, no. 2, pp. 189-194, 2011.
[24] X. Li, G. Yang, L. Xu *et al.*, "Characterization of dry biopotential electrodes." pp. 1478-1481.
[25] P. Trigueiros, F. Ribeiro, and L. P. Reis, *Hand Gesture Recognition System Based in Computer Vision and Machine Learning*, 2015.
[26] Z. Yang, R. Xiao, and C. Harrison, “Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography,” in 29th Annual Symposium on User Interface Software and Technology, 2016, pp. 843-850.